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The jobs of unmanned aerial system/remotely piloted aircraft (UAS/RPA) pilot and sensor operator (SO) are relatively new in aviation and views on who is best suited to fill these positions are evolving. There are few published studies that have examined the entry requirements for UAS/RPA training or the predictive utility of selection methods. In the US Air Force (USAF) selection methods and aptitude requirements for UAS/RPA pilots are very similar to those for manned aircraft pilots and have shown similar levels of predictive validity for both. USAF SOs are enlisted aviators who work side-by-side with UAS/RPA pilots, providing assistance with all aspects of aircraft employment and sensor management. Qualification for SO training involves medical, citizenship, and security standards and aptitude requirements (Armed Services Vocational Aptitude Battery [ASVAB]). The current study examined the predictive validity of the ASVAB for SO training grades. Participants were students enrolled in three SO courses (Basic Sensor Operator Course [BSOC] n = 461, MQ-1 Initial Qualification Requirements Training [MQ-1 IQRT] n = 430, or MQ-9 Initial Qualification Training MQ-9 [IQRT], n = 249). The training criterion was average grade on written tests. The two ASVAB composites used for SO training qualification (General and Electronics) demonstrated good predictive validity for all three courses (BSOC, .541 and .535; MQ-1 IQRT, .583 and .553; MQ-9 IQRT,
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**Predictive Validity of UAS/RPA Sensor Operator Training Qualification Measures**

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Abstract

US Air Force sensor operators (SOs) are enlisted aviators who work side-by-side with unmanned aerial systems/remotely piloted aircraft (UAS/RPA) pilots, providing assistance with all aspects of aircraft employment and sensor management. SO training qualification includes medical, citizenship, and security standards and aptitude requirements. The current study examined the validity of the Armed Services Vocational Aptitude Battery (ASVAB) for predicting grades of students in three SO courses. The ASVAB composites used for SO training qualification (General and Electronics) demonstrated good predictive validity for all three courses (corrected for range restriction and criterion unreliability): Basic Sensor Operator Course, n = 461, $r$ = .541 and .535; MQ-1 Initial Qualification/Requalification Training, n = 430, $r$ = .583 and .553; MQ-9 Initial Qualification/Requalification Training, n = 249, $r$ = .357 and .334). Although current selection methods are effective, based on results of UAS/RPA job/task analyses, the Air Force is examining the utility of other measures to supplement the ASVAB.

Key Words: unmanned aerial systems, remotely piloted aircraft, sensor operators, personnel selection, Armed Services Vocational Aptitude Battery

# Predictive Validity of UAS/RPA Sensor Operator Training Qualification Measures

The jobs of unmanned aerial system/remotely piloted aircraft (UAS/RPA) pilot and sensor operator are relatively new in aviation and views on who is best suited to fill these positions are evolving (Carretta, Rose, & Bruskiewicz, in press). The US military employs several UAS/RPA systems which vary in size, configuration, and characteristics. There are few published studies that have examined the entry requirements for UAS/RPA training or the predictive utility of selection methods (for a review see Carretta et al., in press).

## US Air Force (USAF) RPA Pilots

USAF RPA pilots are a mix of 1) rated officers trained to fly medium-altitude, weaponized aircraft (HQ AFPC/DPSIDC, 2011a) who have been retrained to operate RPAs and 2) officers with no prior operational flying experience who have completed the Undergraduate RPA Training (URT) course. Currently, the majority of new USAF RPA pilots are URT graduates with the remainder coming from retrained experienced pilots.

Selection methods and aptitude requirements for URT are very similar to those for manned aircraft pilot training (Carretta, 2013; Rose, Arnold, & Howse, 2013). Although selection factors vary by officer commissioning source, medical flight screening and aptitude testing are two important factors. Medical Flight Screening (MFS) includes successful completion of an FAA Class III Medical Certificate and an USAF Flying Class IIU Medical Examination (United States Air Force, 2011), review of medical records, psychological testing, and an interview. A licensed psychologist uses clinical judgment to assess the psychological disposition of URT applicants to determine whether there is a medically disqualifying condition in compliance with Air Force guidelines (United States Air Force, 2011). Aptitude testing includes the Air Force Officer Qualifying Test (AFOQT; Drasgow, Nye, Carretta, & Ree, 2011), Test of Basic Aviation Skills (TBAS; Carretta, 2005), and Pilot Candidate Selection Method (PCSM; Carretta, 2011). Minimum qualifying scores for URT have been established for both the AFOQT and PCSM and are identical to those for manned aircraft pilot training (United States Air Force, 2014).

**US Air Force – Sensor Operators**

In 2009, the USAF also created the UAS Sensor Operator (SO) career field (1U0X1). Sensor operators are enlisted aviators who work side-by-side with RPA pilots, providing assistance to the pilot with all aspects of aircraft employment and sensor systems management (HQ AFPC/DPSIDC, 2011b). They are responsible for the employment of airborne sensors in manual or computer-assisted modes to acquire, track, and monitor airborne, ground, and maritime objects. Sensor operators assist RPA pilots through all phases of employment including mission planning, flight operations, and debriefings. They continually monitor aircraft and weapons systems status to ensure lethal and non-lethal application of airpower. Currently, USAF 1UOX1 specialists perform their duties on the MQ-1 Predator and the MQ-9 Reaper RPAs. Selection for enlisted SOs is based on medical qualification (United States Air Force, 2011), US citizenship, eligibility for a Top Secret clearance, and scores on the Armed Services Vocational Aptitude Battery (ASVAB; Segall, 2004), the US military enlistment qualification and training classification test. Courses in chemistry, computer science, earth sciences, geography, and math are desirable.

**Job/Task Analyses**

Several studies have examined UAS/RPA job requirements and the critical skills, abilities, and other characteristics (SAOCs) needed to perform them. In 1979, the US Army Research Institute for the Behavioral and Social Sciences (ARI) conducted individual structured interviews with UAS test system personnel (operators, support personnel, and supervisors) as part of a research program to establish selection criteria for UAS personnel (Crumley & Bailey, 1979). These data were used to guide structured group interviews with UAS operators.

Results showed that both the air vehicle operator (AVO) and sensor operator (SO) jobs required average or above-average hand/eye coordination, verbal communication skill, logic, and patience, but lower levels of color vision, endurance, hearing acuity, and physical strength. Further, AVOs and SOs were found to have distinct personality characteristics. AVOs tended to like the logic, planning, and sequential steps of the position, whereas sensor operators tended to prefer the excitement, uncertainty, and unpredictability associated with the task. Finally, both AVOs and SOs expressed dislike for close supervision during missions, but nevertheless favored having a third (artillery trained) person in the Ground Control Station (Crumley & Bailey, 1979).

US Air Force and UK Royal Air Force studies also have found overlap in the entry-level SAOCs required for RPA pilots and SOs (e.g., see Carretta et al., in press or Howse, 2011 for a review). For example, results of job analyses have shown central information processing (e.g., timesharing), perceptual and psychomotor abilities, spatial and symbolic reasoning, situational awareness, and working memory to be essential for RPA pilot and sensor operator performance (Bailey, 2008; Chappelle, McDonald, & King, 2010; Chappelle, McDonald, & McMillan, 2011; Paullin, Ingerick, Trippe, & Wasko, 2011).

**Predictive Validation Studies**

Three recent studies have examined the predictive validity of aptitude and personality measures for URT (Carretta, 2013; Chappelle, McDonald, Heaton, Thompson, & Haynes, 2012; Rose, Barron, Carretta, Arnold, & Howse, 2014). Carretta (2013) examined the predictive validity of the AFOQT Pilot and PCSM composites for URT completion (pass/fail) for a sample of 139 students. Moderate validities for the AFOQT Pilot ($r$ = .378, p < .001) and PCSM ($r$ = .480, p < .001) composites were observed for URT completion. The correlations increased after correction for direct range restriction (Thorndike, 1949) and dichotomization (Cohen, 1983) of the URT pass/fail criterion (AFOQT Pilot, $r$ = .57; PCSM, $r$ = .68). Students with PCSM scores at or below the 25$^{th}$ percentile had a 52.2% failure rate. Those with PCSM scores at or above the 75$^{th}$ percentile had only a 7.8% failure rate.

Chappelle et al. (2012) and Rose et al. (2014) explored the utility of using a combination of cognitive and personality scores to predict URT performance. In a sample of 117 URT students, Chappelle et al. examined the predictive validity of the AFOQT Pilot composite, Revised NEO Personality Inventory (NEO-PI-R; Costa & McCrae, 1992), and a neuropsychological battery, the MicroCog (Powell, Kaplan, Whitla, Weintraub, Catlin, & Funkenstein, 2004) versus URT completion. The regression-weighted composite that best predicted URT completion included the AFOQT Pilot composite, several NEO-PI-R scales, and the MicroCog Reaction Time subtest. Discriminant analyses showed that personality scores improved classification accuracy (identification of true positives and true negatives) beyond that provided by cognitive ability and prior flight time. When personality scores were included classification accuracy improved from 57.1% to 75.2%; however, these results likely capitalized on chance given the large number of NEO-PI-R scales relative to the small sample size.

Rose et al. (2014) evaluated the extent to which scores from a Big Five measure of personality, the Self-Description Inventory+ (SDI+; Manley, 2011) could improve prediction of URT outcomes beyond updated versions of the AFOQT Pilot and PCSM composites. Participants were 170 URT students with RPA Initial Flight Screening (RFS) outcomes and 110 students with RPA Instrument Qualification (RIQ) outcomes. Both RFS and RIQ emphasize development of skills traditionally required for manned aircraft pilots, also considered essential for USAF RPA pilots. Training criteria were RFS completion (pass/fail) and several measures involving RIQ academic and simulator grades. Data for all analyses were corrected for direct range restriction (Thorndike, 1949). Data for analyses involving the RFS completion (pass/fail) criterion were corrected both for direct range restriction and dichotomization (Cohen, 1983). Results for the RFS completion criterion were similar to those reported by Carretta (2013). Correlations between the updated AFOQT and PCSM composites and RFS completion were statistically significant (AFOQT Pilot, $r$ = .38, p < .001; PCSM, $r$ = .48, p < .001). Correlations increased after correction for direct range restriction and dichotomization of the RFS pass/fail criterion (AFOQT Pilot, $r$ = 48; PCSM, $r$ = .67). Analyses involving personality scores from the SDI+ showed no incremental validity when used in combination with the AFOQT Pilot or PCSM composites for predicting RFS completion. However, the SDI+ Openness score demonstrated small, but statistically significant incremental validity for predicting overall RIQ course grades aggregated across academic and simulated flying performance.

### Purpose

To date, no studies have been reported that examine the predictive validity of selection methods for USAF UAS/RPA sensor operators. The purpose of the current study is to examine the predictive utility of cognitive ability and technical knowledge scores for three sensor operator training courses.

## Method

### Participants

Three separate validation studies were conducted. The samples consisted of enlisted personnel enrolled in the Basic Sensor Operator Course (BSOC, n = 461), MQ-1B Initial Qualification and Requalification Training course (MQ-1 IQRT, n = 430), or the MQ-9 Initial Qualification and Requalification Training course (MQ-9 IQRT, n = 249). To qualify for entrance into the US Air Force, applicants must achieve a score at or above the 36th percentile on the ASVAB AFQT composite[1]. Aptitude requirements for sensor operator (1U0X1) training are a score at or above the 64th percentile on the USAF ASVAB General composite or a score at or above the 54th percentile on the Electronics composite[2]. Demographic information was not available for all participants. However, for those reporting demographic data, the results were similar across the three samples. The participants were predominantly male (84.5 % to 90.2%), White (80.0% to 90.1%), and non-Hispanic (79.8% to 82.4%). The mean ages for the samples ranged from 19.1 to 20.7 years.

## Measures

**Armed Services Vocational Aptitude Battery (ASVAB).** The ASVAB (Segall, 2004) is used for enlistment qualification and classification into training specialties by all branches of the US military. It consists of 9 tests: General Science (GS), Arithmetic Reasoning (AR), Word Knowledge (WK), Paragraph Comprehension (PC), Auto and Shop Information (AS), Mathematics Knowledge (MK), Mechanical Comprehension (MC), Electronics Information (EI), and Assembling Objects (AO). The two verbal (WK, PC) and two math (AR, MK) tests contribute to the Armed Forces Qualification Test (AFQT) composite, which is used by all

[1] The AFQT (Armed Forces Qualification Test) is a weighted composite of the ASVAB Verbal (VE) composite (Paragraph Comprehension and Word Knowledge tests) and math tests (Arithmetic Reasoning and Math Knowledge).

[2] The USAF General composite combines the Arithmetic Reasoning (AR) test and Verbal (VE) composite. The Electronics composite combines the General Science (GS), Arithmetic Reasoning (AR), Math Knowledge (MK), and Electronics Information (EI) tests (Segall, 2004).

branches of the US military for enlistment qualification. Each military service branch creates its own set of composites used to qualify enlistees into training specialties. The US Air Force uses four classification composites: Mechanical, Administrative, General, and Electronics. The ASVAB has been validated for training (Ree & Earles, 1991; Ree, Carretta, & Doub, 1998/1999) and job performance (Ree, Earles, & Teachout, 1994).

**UAS/RPA sensor operator training criteria**. The UAS/RPA sensor operator (1U0X1) training path begins with the Aircrew Fundamentals course at Joint Base San Antonio (JBSA)-Lackland, TX. The course is 6 days long and prepares enlisted personnel for their transition to a career in aviation. This course screens for the ability to handle the rigor of aircrew duties prior to candidates entering expensive follow-on training (United States Air Force, 2012). Next, students complete the RPA Basic Sensor Operator Course (BSOC) at JBSA-Randolph, TX. This 6 week course provides instruction to students in areas such as RPA crew duties, types of sensors, exposure to weapons, and geospatial reference systems. Following BSOC, sensor operators attend MQ-1 or MQ-9 Formal Training located at Holloman AFB, NM, March ARB, CA, or Hancock Field in Syracuse, NY. At the Formal Training Units, sensor operators undergo the MQ-1 or MQ-9 Initial Qualification Course lasting approximately three to four months. The MQ-1 and MQ-9 courses are designed to produce basic mission capable aircrew in MQ-1 and MQ-9 operations, respectively, and provide training in areas such as intelligence, surveillance, and reconnaissance (ISR), close air support (CAS), and combat search and rescue (CSAR). The MQ-1 and MQ-9 courses also are used to provide requalification or transition training for MQ-1 or MQ-9 sensor operators that have been unqualified for over eight years. Graduates from the Formal Training Units move to their combat squadrons, go through a combat mission-ready certification, and then become line flyers.

Training performance criteria were collected for three courses: Basic Sensor Operator Course (BSOC, n = 461), MQ-1B Initial Qualification and Requalification Training (MQ-1 IQRT, n = 430) or MQ-9 Initial Qualification and Requalification Training (MQ-9 IQRT, n = 249) courses. The training criterion for the BSOC course was the average grade for all written tests across all training blocks. The criterion for the MQ-1 IQRT and MQ-9 IQRT courses was a 4-point final grade coded as (1) fail, (2) pass, (3) satisfactory, or (4) outstanding.

**Analyses**

Analyses were conducted by training course. They began with an examination of the descriptive statistics for the selection test scores and training grades. Three sets of correlations were examined: observed (uncorrected) correlations, correlations corrected for multivariate range restriction (Lawley, 1943), and correlations corrected for both range restriction and reliability (Hunter & Schmidt, 2004) of the criterion. The assumptions underlying range restriction correction are the same as two of the three assumptions underlying the computation of a Pearson product-moment correlation - linearity of form and homoscedasticity. If the assumptions are met to estimate the correlation coefficient, they also are met to compute the correction. The corrected means, standard deviations, and correlations are superior estimates of the population values compared to the uncorrected values. This method removes the bias from the uncorrected sample estimates.

The range-restriction-corrected correlations were then corrected for reliability of the training grades ($r_c = \frac{r_{xy}}{\sqrt{r_{yy}}}$.). The reliability of the pilot training grades was estimated to be .80 based on results from similar studies that examined academic grades (Kuncel, Hezlett, & Ones, 2004). The correlations were not corrected for the reliability of *both* the test scores and criterion because we were interested in the specific predictors (ASVAB scores) and not the theoretical constructs underlying them (cognitive ability). This third set of correlations provides a theoretical estimate of the validities of the predictors when a perfectly reliable criterion is available.

Finally, stepwise regression analyses were conducted to identify the best combination of ASVAB tests for predicting training grades for each course. After the best combination of ASVAB tests had been identified, the data were corrected for range restriction and reliability of the training grades. Cross-validation shrinkage was estimated for these models using a non-sampling approach (Stein, 1960). Stein's (1960) equation has the advantage of providing an estimate of average cross-validity based on the largest available sample.

## Results

### Means and SDs

Table 1 summarizes the means and SDs for the test scores and training grades by course. Similar results were observed for each course. The mean ASVAB scores were range-restricted compared to the normative values where the means and SDs are 50 and 10 for the tests and 50 and 28.29 for the composites. For the General (G) and Electronics (E) composites which are used to qualify applicants for SO training, the means across the three courses were on average 0.77 (G) and 0.89 (E) SDs above the normative values and the variances were on average 32.2% (G) and 24.2% (E) of the normative values.

[Insert Table 1 about here]

### Correlations

Table 2 summarizes the correlational analyses. For the ASVAB composites, 14 of 15 observed validities were statistically significant for the three training grades. Cohen (1988) characterizes correlations of .10 as small, .30 as medium, and .50 or greater as large. The observed validities for the General (G) and Electronics (E) composites were small for all three courses. After correction for range restriction and reliability of the training grades, the validities for the G and E composites were in the moderate to strong range (Cohen, 1988) for all three courses. They were .541 and .535 for the BSOC, .583 and .553 for the MQ-1 IQRT, and .357 and .334 for the MQ-9 IQRT courses. On the test level, 24 of 27 observed validities were statistically significant. As with the composite scores, the observed validities for the tests were small, but were moderate or large after correction for range restriction and reliability of the training grades.

**Regression Analyses**

Stepwise regression analyses were conducted to determine the best combination of ASVAB tests for predicting training grades for each course. These analyses identified different best-fitting regression models for the three courses. For the BSOC course, the best-fitting model included GS, AR, AS, and VE with $R = .366$. After correction for range restriction, the R increased to .543, and after correction for both range restriction and reliability of the training grades it increased to .607. The cross-validity of the fully-corrected model was estimated (Stein, 1960) to be .596. The estimated cross-validities for the ASVAB G and E composites were .536 and .530.

The stepwise regression for the MQ-1 IQRT course yielded a model with two test scores, MK and VE, with $R = .236$[3]. The R increased to .562 after the correlations were corrected for range restriction and to .628 after correction for both range restriction and reliability of the criterion. The estimated cross-validities were .596 for the test score model, .579 for G, and .548

[3] The MK and VE scores are the components of the USAF Administrative composite. The increment in predictive validity for the stepwise regression model compared to the Administrative composite occurs because weights for these scores are optimized in the stepwise regression model for predicting the MQ-1 IQR training grade.

for E. For the MQ-9 IQRT criterion, the stepwise regression model included only one ASVAB test, AS, which yielded a correlation of .192. The correlation increased to .268 after correction for range restriction and to .333 after correction for both range restriction and unreliability of the training grades. The cross-validities were .314 for AS, .341 for G, and .337 for E.

The stepwise models produced higher correlations for the training grades than did the ASVAB G and E composites for the BSOC and MQ-1 IQRT courses, but not for the MQ-9 IQRT course. The small differences in predictive validity for the best-fitting test score models and ASVAB composites and the lack of a common best-fitting model for the three courses suggests that the current composites should be retained for now.

## Discussion

Consistent with prior ASVAB validation studies involving other Air Force career fields (Ree & Earles, 1991; Ree et al., 1994, 1998/1999), test scores were predictive of training performance for sensor operator training. After correction, validities were in the moderate to large range (Cohen, 1988) for the ASVAB composites and tests.

Both observed and corrected validities tended to be lower for the MQ-9 IQRT course compared with the other two courses. The reason for this is unknown, but may in part be because the MQ-9 IQRT course occurs later in the training sequence where the impact of cognitive ability and technical knowledge measured by the ASVAB are mitigated by the effects of training (weaker students have been eliminated, acquisition of job-specific knowledge and skills).

Results of UAS/RPA job/task analyses (Bailey, 2008; Crumley & Bailey, 1979; Chappelle et al., 2010, 2011; Howse, 2011; Paullin et al., 2011) have identified several critical sensor operator SAOCs not adequately measured by the ASVAB. Critical skills and abilities not measured by the ASVAB include logic, perceptual and psychomotor, spatial and symbolic reasoning, situation awareness, verbal communication, and working memory. Other critical characteristics not measured by the ASVAB include work environment preferences associated with sensor operator tasks (e.g., preferences for excitement, uncertainty, and unpredictability of the task) and personality traits (e.g., patience). Several measures have been developed to address these gaps in measurement. Measures of non-verbal reasoning and working memory have been developed as potential additions to the ASVAB; however, to date, data collection and psychometric studies have not been completed. The Air Force Personnel Center (AFPC) has begun data collection for sensor operator trainees on the Test of Basic Aviation Skills (TBAS, Carretta, 2005) which includes measures of psychomotor and spatial ability. AFPC also has completed initial development of measures of person-environment fit and multitasking which may have applicability for UAS/RPA sensor operators. Finally, data collection has begun for two personality tests, the Tailored Adaptive Personality Assessment System (TAPAS; Knapp, Heffner, & White, (2011) and the Self-Description Inventory (SDI+, Manley, 2011). The utility of these measures will be examined in future studies as data become available.

## Potential Changes in Job and SAOC Requirements as Technology Matures

As technology matures it is expected that the roles played by UAS/RPA pilots and sensor operators will change. UAS/RPA will become more automated and autonomous, requiring less emphasis on active control (hands-on flying and maneuvering of sensors) and more on supervisory control and operator-machine teaming. For example, General Atomics Aeronautical (2014) recently demonstrated an advanced cockpit ground control station with improved graphics and video designed to enable interoperability and compatibility across UAS/RPA systems. Increased automation and autonomy may enable combination of the pilot and sensor operator roles and perhaps allow a single operator to exert supervisory control over multiple systems. In such a scenario, cognitive ability and job knowledge likely will remain important, with less emphasis on psychomotor ability. Further, the ideal personality profile for someone exerting supervisory control as opposed to active control may be different and should be examined (King, 2000).

Implications of technology advances should be monitored closely, along with changes in the core duties of the SO role and an understanding of the attributes required to successfully perform them.

**References**

Bailey, M. (2008). *Predator pilot and sensor operator selection test batteries.* Cranwell, UK: Royal Air Force College.

Carretta, T. R. (2005). *Development and validation of the Test of Basic Aviation Skills (TBAS),* AFRL-HE-WP-TR-2005-0172. Wright-Patterson AFB, OH: Air Force Research Laboratory, Human Effectiveness Directorate, Warfighter Interface Division.

Carretta, T. R. (2011). Pilot Candidate Selection Method: Still an effective predictor of US Air Force pilot training performance. *Aviation Psychology and Applied Human Factors, 1,* 3-8.

Carretta, T. R. (2013). Predictive validity of pilot selection instruments for remotely piloted aircraft training outcome. *Aviation, Space, and Environmental Medicine, 84,* 47-53.

Carretta, T. R., Rose, M. R., & Bruskiewicz, K. T. (in press). Selection methods for unmanned aerial systems/ remotely piloted aircraft operators. In N. J. Cooke, L. Rowe, & W. Bennett (Eds.), *Remotely piloted aircraft: A human systems integration perspective* (pp. xxx-yyy). Hoboken, NJ: Wiley.

Chappelle, W., McDonald, K., Heaton, J. N., Thompson, W., & Haynes, J. (2012). *Neuropsychological and personality attributes distinguishing high vs. low training performance of MQ-1B pilot trainees.* Paper presented at the Aerospace Medicine Association Annual Conference, Atlanta, GA.

Chappelle, W., McDonald, K., & King, R. E. (2010). *Psychological attributes critical to the performance of MQ-1 Predator and MQ-9 Reaper U.S. Air Force sensor operators,* AFRL-SA-BR-TR-2010-0007. Brooks City Base, TX: USAF School of Aerospace Medicine, Aerospace Medical Consultation Division.

Chappelle, W., McDonald, K., & McMillan, K. (2011). *Important and critical psychological attributes of USAF MQ-1 Predator and MQ-9 Reaper pilots according to subject matter experts,* AFRL-SA-WP-TR-2011-0002. Wright-Patterson AFB, OH: USAF School of Aerospace Medicine, Aerospace Medicine Consultation Division.

Cohen, J. (1983). The cost of dichotomization. *Applied Psychological Measurement, 7,* 249-253.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences (2nd ed.)*. Mahwah, NJ: Erlbaum.

Costa, P. T., Jr., & McCrae, R. R. (1992). *NEO PI-R professional manual*. Odessa, FL: Psychological Assessment Resources, Inc.

Crumley, L. M., & Bailey, J. P. (1979). *Summary of the results of structured interviews of remotely piloted vehicle system operators* (Working Paper No. FSFU 79-1). Fort Sill, OK: U.S. Army Research Institute for the Behavioral and Social Sciences Fort Sill Field Unit.

Drasgow, F., Nye, C. D., Carretta, T. R., & Ree, M. J. (2010). Factor structure of the Air Force Officer Qualifying Test form S: Analysis and comparison with previous forms. *Military Psychology*, *22*, 68-85.

General Atomics Aeronautical (2014). *GA-ASI demonstrates advanced cockpit GCS at Farnborough [*Press Release]. Retrieved from http://www.gaasi.com/news_events/index.php?read=1&id=438.

Howse, W. R. (2011). *Knowledge, skills, abilities, and other characteristics for remotely piloted aircraft pilots and operators* (AFCAPS-FR-2011–0006). Randolph AFB, TX: HQ AFPC/DSYX Strategic Research and Assessment Branch.

HQ AFPC/DPSIDC. (2011a). *Air Force officer classification directory (AFOCD): The official* *guide to the Air Force officer classification codes.* Randolph AFB, TX: Author.

HQ AFPC/DPSIDC. (2011b). *Air Force enlisted classification directory (AFECD): The official guide to the Air Force enlisted classification codes.* Randolph AFB, TX: Author.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis.* Thousand Oaks, CA: Sage.

King, R.E. (2000). Remote operators: Empirically validating a comprehensive screening program to help counter an increasingly hostile aerial environment. *Countering the Directed Energy Threat: Are Closed Cockpits the Ultimate Answer?* RTO Meeting Proceedings 30.

Knapp, D. J., Heffner, T. S., & White, L. (Eds.) (2011). *Tier one performance screen initial operational test and evaluation: Early results*, ARI TR-1283. Alexandria, VA: United States Army Research Institute for the Behavioral and Social Sciences.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology, 86*, 148-161.

Lawley, D.N. (1943). A note on Karl Pearson's selection formulae. *Proceedings of the Royal Society of Edinburgh*, LXII-Part 1, 19-32.

Manley, G. G. (2011). *Development of domain and facet level scales for the Self-Description Inventory*, AFCAPS-FR-2011-0007, Randolph AFB, TX: Air Force Personnel Center, Strategic Research and Assessment Branch.

Paullin, C., Ingerick, M., Trippe, D.M., & Wasko, L. (2011). *Identifying best bet entry-level selection measures for US Air Force remotely piloted aircraft (RPA) and sensor operator occupations* (FR-11-64). Randolph AFB, TX: HQ AFPC/DSYX Strategic Research and Assessment Branch.

Powell, D., Kaplan, E., Whitla, D., Weintraub, S., Catlin, R., & Funkenstein, H. (2004). *MicroCog: Assessment of cognitive functioning Windows ed*. San Antonio, TX: Pearson.

Ree, M. J., Carretta, T. R., & Doub, T. W. (1998/1999). A test of three models of the role of *g* and prior job knowledge in the acquisition of subsequent job knowledge in training. *Training Research Journal, 4,* 135-150.

Ree, M. J., & Earles, J. A. (1991). Predicting training success: Not much more than *g*. *Personnel Psychology, 44*, 321-332.

Ree, M. J., Earles, J. A., & Teachout, M. S. (1994). Predicting job performance: Not much more than *g*. *Journal of Applied Psychology*, *79,* 518-524.

Rose, M. R., Arnold, R. D., & Howse, W. R. (2013). Unmanned aircraft systems selection practices: Current research and future directions. *Military Psychology*, 413-427.

Rose, M. R., Barron L, G., Carretta, T. R., Arnold, R. D., & Howse, W. R. (2014). Early identification of unmanned aircraft pilots using measures of personality and aptitude, *International Journal of Aviation Psychology, 24*, 35-52.

Segall, D. O. (2004). *Development and evaluation of the 1997 ASVAB score scale,* Technical Report No. 2004-002. Seaside, CA: Defense Manpower Data Center.

Stein, C. (1960). Multiple regression. In I. Olkin *et al*. (Eds.), *Contributions to probability and statistics*. Stanford, CA: Stanford University Press.

Thorndike, R. L. (1949). *Personnel selection.* NY: Wiley.

United States Air Force (2011). *Medical examinations and standards* (AFI-48-123). Washington, DC: Author.

United States Air Force (2012). *1U0X1: Remotely piloted aircraft sensor operator (RPA SO): Career field education and training plan.* Washington D.C.: Author.

United States Air Force (2014). *Air Force Strategic Personnel Assessment Program* (AFI-36-2136). Washington, DC: Author.

**Table 1. Means and SDs for Selection Test Scores and Training Grades by Course**

| Score | Abbrev. | BSOC | | MQ-1 IQRT | | MQ-9 IQRT | |
|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD |
| Armed Forces Qualification Test | AFQT | 72.00 | 14.70 | 74.69 | 14.11 | 72.50 | 14.25 |
| Mechanical | M | 68.99 | 19.03 | 70.88 | 19.41 | 68.12 | 19.14 |
| Administrative | A | 73.42 | 14.05 | 75.86 | 13.39 | 74.08 | 13.46 |
| General | G | 70.87 | 16.35 | 73.43 | 15.78 | 71.01 | 16.38 |
| Electronics | E | 75.97 | 14.22 | 73.43 | 14.21 | 76.55 | 13.56 |
| General Science | GS | 56.36 | 6.15 | 56.86 | 6.33 | 56.41 | 6.36 |
| Arithmetic Reasoning | AR | 56.78 | 6.05 | 57.31 | 6.03 | 56.80 | 5.75 |
| Word Knowledge | WK | 53.79 | 5.87 | 55.00 | 6.14 | 53.93 | 6.21 |
| Paragraph Comprehension | PC | 56.01 | 5.18 | 56.68 | 5.40 | 55.97 | 5.17 |
| Math Knowledge | MK | 58.29 | 5.14 | 58.76 | 5.10 | 58.68 | 5.01 |
| Electronics Information | EI | 56.07 | 7.82 | 56.86 | 8.11 | 56.57 | 7.89 |
| Auto & Shop Information | AS | 51.73 | 8.51 | 52.11 | 8.77 | 51.18 | 8.40 |
| Mechanical Comprehension | MC | 57.85 | 7.55 | 57.38 | 7.60 | 57.26 | 5.81 |
| Assembling | AO | 59.00 | 6.16 | 58.34 | 6.37 | 58.71 | 6.14 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Objects | | | | | | |
| Avg. Training Grade | 95.91 | 2.77 | 3.16 | 0.54 | 2.95 | 0.75 |

Note. The sample sizes were: BSCC (461), MQ-1 IQRT (430), and MQ-9 (249). Not all participants were administered a version of the ASVASB that included the AO subtest. The sample sizes for AO were: BSOC (107), MQ1-IQRT (391), and MQ9-IQRT (220).

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**Table 2. Observed and Corrected Correlations between ASVAB Scores and Training Grades**

| Score | BSOC (n = 461) | | | MQ-1 IQRT (n = 430) | | | MQ-9 IQRT (n = 249) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $r$ | $r_c$ | $r_{fc}$ | $r$ | $r_c$ | $r_{fc}$ | $r$ | $r_c$ | $r_{fc}$ |
| AFQT | .245[c] | .473 | .528 | .218[c] | .544 | .608 | .154[a] | .302 | .337 |
| M | .336[c] | .525 | .586 | .195[c] | .499 | .557 | .223[c] | .348 | .389 |
| A | .207[c] | .451 | .504 | .231[c] | .549 | .613 | .114 | .278 | .310 |
| G | .261[c] | .484 | .541 | .187[c] | .522 | .583 | .179[b] | .320 | .357 |
| E | .244[c] | .479 | .535 | .188[c] | .495 | .553 | .160[a] | .299 | .334 |
| GS | .119[b] | .390 | .436 | .178[c] | .481 | .537 | .106 | .265 | .296 |
| AR | .247[c] | .473 | .528 | .118[a] | .436 | .487 | .135[a] | .281 | .314 |
| WK | .193[c] | .413 | .461 | .184[c] | .522 | .583 | .169[b] | .315 | .352 |
| PC | .182[c] | .429 | .479 | .203[c] | .526 | .588 | .125[a] | .285 | .318 |
| MK | .135[b] | .393 | .439 | .151[b] | .456 | .509 | .009 | .196 | .219 |
| EI | .207[c] | .422 | .471 | .097[a] | .341 | .381 | .155[a] | .283 | .316 |
| AS | .282$_{c}$ | .408 | .456 | .118[a] | .242 | .270 | .192[b] | .268 | .333 |
| MC | .258[c] | .443 | .495 | .162[c] | .368 | .411 | .161[a] | .263 | .294 |
| AO | .082 | .445 | .494 | .184[c] | .555 | .620 | .117 | .322 | .360 |

Notes. The columns labeled “r” are observed correlations, while those labeled “$r_c$” were corrected for range restriction, and those labeled “$r_{fc}$” were corrected for both range restriction and reliability of the training grades. Not all participants were administered a version of the ASVASB that included the AO subtest. The sample sizes for the AO score were 107 for BSOC, 391 for MQ-1 IQRT, and 220 for MQ-9 IQRT.

[a]$p \leq .05$; [b]$p \leq .01$; [c]$p \leq .001$